CALENDAR ANOMALIES

IN THE RUSSIAN STOCK MARKET

Guglielmo Maria Caporale

Brunel University London

and

Valentina Zakirova

Higher School of Economics, Moscow

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Abstract

This paper investigates whether or not calendar anomalies (such as the January, day-of-the-week and turn-of-the-month effects) characterise the Russian stock market, which could be interpreted as evidence against market efficiency. Specifically, OLS, GARCH, EGARCH and TGARCH models are estimated using daily data for the MICEX market index over the period 22/09/1997-14/04-2016. The empirical results show the importance of taking into account transactions costs (proxied by the bid-ask spreads): once these are incorporated into the analysis calendar anomalies disappear, and therefore there is no evidence of exploitable profit opportunities based on them that would be inconsistent with market efficiency.

Keywords: calendar effects, Russian stock market, transaction costs

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Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University London, UB8 3PH, UK.

Email: Guglielmo-Maria.Caporale@ brunel.ac.uk

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1 Introduction

There is a large literature testing for the presence of calendar anomalies (such as the "day-of-the-week", “day-of-the-month” and "month-of-the-year” effects) in asset returns. Evidence of this type of anomalies has been seen as inconsistent with the efficient market hypothesis (EMH – see Fama, 1965, 1970 and Samuelson, 1965), since it would imply that trading strategies exploiting them can generate abnormal profits. However, a serious limitation of many studies on this topic is that they neglect transaction costs: broker commissions, spreads, payments and fees connected with the trading process may significantly affect the behaviour of asset returns and calendar anomalies might disappear once they are taken into account, the implication being that in fact there are no exploitable profit opportunities based on them that would negate market efficiency.

The present study examines calendar anomalies in the Russian stock market incorporating transaction costs in the estimated models (following Gregoriou et al., 2004 and Caporale et al., 2015), and therefore it improves on previous studies on anomalies in this market, such as Compton (2013), not taking into account transaction costs. Specifically, four models are estimated: OLS, GARCH, TGARCH, EGARCH.

The structure of the paper is the following: Section 2 reviews briefly the literature on calendar anomalies; Section 3 describes the data and outlines the methodology; Section 4 presents the empirical findings; Section 5 offers some concluding remarks.

2 Literature Review

The existence of a January effect had already been highlighted by studies such as Rozeff and Kinney (1976) and Lakonishok and Smith (1988) using long series to avoid the problems of data snooping, noise and selection bias, and finding evidence of various calendar anomalies, namely January, day-of-the-week and turn-of-the-month effects. Thaler (1987) reported that the January effect characterises mainly shares of small companies, whilst Kohers and Kohli (1991) concluded that it is also typical of shares of large companies. Cross (1973) was one of the first to identify a day-of-the-week effect. Gibbons and Hess (1981) found the lowest returns on Mondays, and the highest on Fridays. Mehdian and Perry (2001) showed a decline of this anomaly over time.

Most existing studies, such as the ones mentioned above, concern the US stock market. Only a few focus on emerging markets. For instance, Ho (1990) found a January effect in 7 out of 10 Asia-Pacific countries; Darrat (2013) analysed an extensive dataset including 34 countries and reported a January effect in all except three of them (Denmark, Ireland, Jordan); Yalcin and Yucel (2003) analysed 24 emerging markets and found a day-of the-week effect in market returns for 11 countries and in market volatility in 15 countries; Compton et al. (2013) focused on Russia and discovered various anomalies (January, day-of-the-week and turn-of-the month effect) in the MICEX index daily returns.

Transaction costs were first taken into account by Gregoriou et al. (2004), who estimated an OLS regression as well as a GARCH (1,1) model and concluded that calendar anomalies (specifically, the day-of-the-week effect) disappear when returns are adjusted using transaction costs. More recently, Caporale et al. (2015) reached the same conclusion in the case of the Ukrainian stock market using a trading robot approach.

Damodaran (1989) argued that the main reason for the weekend effect (low returns on Mondays and high returns of Fridays) is the arrival of negative news at the beginning of the week. However, Dubois and Louvet (1996) found that in other markets such as France, Turkey, Japan, Singapore, Australia the highest negative returns appear on Tuesdays; this may be explained by the fact that these markets are influenced by US negative news with a one-day lag. Keef and McGuinness (2001) suggested that the settlement procedure could be the explanation for negative returns on Mondays (see also Kumari and Mahendra, 2006); however, these might differ across countries. Rystrom and Benson (1989) argued that investors are irrational and their sentiment depends on the day of the week, which might be the explanation for the day-of-the week effect. Finally, Pettengill (2003) claimed that they behave differently on Mondays because of scare trading, with informed investors shorting because of negative news from the weekend.

3 Data and Methodology

3.1 Data

The series analysed is the capitalisation-weighted MICEX market index. The sample includes 4633 observations on (close-to-close) daily returns and covers the period from 22/09/1997 (when this index was created) till 14/04/2016. We also use bid and ask prices to calculate the bid-ask spread as a proxy for transaction costs. The data source for the index is Bloomberg,

Returns were calculated using the following formula:

$$R_t = \frac{P_t^{close} - P_{t-1}^{close}}{P_{t-1}^{close}},$$

where P_t is the index value in period t. Dividends are not included because the trading strategy considered is daily.

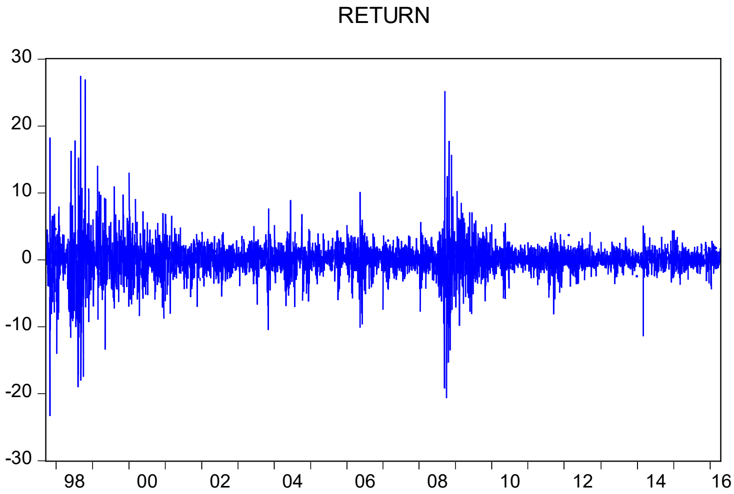
The data source for bid-ask prices is Thompson Reuters. Since the MICEX index is a composite index of 50 Russian tradable companies, the bid-ask spread was calculates as a weighted spread of the individual stocks, using the following formula:

$$S = \omega_1 S_1 + \omega_2 S_2 + \cdots + \omega_{49} S_{49} + \omega_{50} S_{50},$$

where S_t is the bid-ask spread used below for adjustment purposes and ω_1 is the share of the stock in the index.

The daily (percentage) return series is plotted in Figure 1. Visual inspection suggests stationary behaviour (also confirmed by unit root tests not reported for reasons of space).

Figure 1 Relative daily returns (%) over time



Following Gregoriou et al. (2004), the adjusted returns were calculated as:

$$RS_t = \frac{(P_t^{close} - S_t) - (P_{t-1}^{close} - S_{t-1})}{(P_{t-1}^{close} - S_{t-1})} \quad (1)$$

where RS_t stands for spread-adjusted returns, R_t for daily returns, and S_t for the bid-ask spread.

The adjustment is motivated by the fact that investors deduct transaction costs from returns to calculate the effective rate of return on their investments. The bid-ask spread is a good proxy for the variable part of transaction costs.

Table 1 reports descriptive statistics for both raw and adjusted returns.

Table 1 Descriptive statistics

	Mean	St. error	Median	Variance	Kurtosis	Skewness	Min	Max
Raw returns	0,10%	0,04%	0,12%	0,07%	0,18	0,84	-20,81%	31,65%
Adjusted returns	0,03%	0,05%	0,09%	1,66%	8,33	0,77	-21,47%	28,16%

It shows that the average return is seven basis points lower for adjusted returns than for raw returns.

3. 2 Methodology

We estimate in turn each of the four models used in previous studies on calendar anomalies, i.e. OLS, GARCH, TGARCH, EGARCH.

3.2.1 January effect

3.2.1.1. OLS Regressions

Following Compton (2013), we run the following regression to test for anomalies:

$$H_0: \beta_1 = \beta_2 =..= \beta_{12}$$

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

where the coefficients $\beta_1 \ldots \beta_{12}$ represent mean daily returns for each month, each dummy variable $D_1 \ldots D_{12}$ is equal to 1 if the return is generated in that month and 0 otherwise, and ε_t is the error term. If the null is rejected we conclude that seasonality is present and run a second regression, namely:

$$H_0: \alpha = 0$$

$$R_t = \alpha + \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{11} D_{11t} + \varepsilon_t,$$

where α stands for January returns, the coefficients $\beta_1 \ldots \beta_{11}$represent the difference between expected mean daily returns for January and mean daily returns for other months, each dummy variable $D_1 \ldots D_{12}$ is equal to 1 if the return is generated in that month and 0 otherwise, and ε_t is the error term.

3.2.1.2 GARCH Model

Given the extensive evidence on volatility clustering in the case of stock returns we follow Levagin (2010), Gregoriou et al. (2004), Yalcin, Yucel (2003), Luo, Gan, Hu, Kao (2009) and Mangala, Lohia (2013) and adopt the following specification.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma * D(Jan)$$

where ω is an intercept, $\varepsilon_t \sim N(0, \sigma_t^2)$ is the error term, and D(Jan) is a series of dummy variables equal to 1 if the return occurs in that month and zero otherwise.

Since σ_t^2 must be positive, we have the following restrictions: $\omega \geq 0, \alpha \geq 0,\ \beta \geq 0.$

3.2.1.3. TGARCH Model

Standard GARCH models often assume that positive and negative shocks have the same effects on volatility, however in practice the latter often have bigger effects. Therefore, following Levagin (2010) we also estimate the following TGARCH model:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 + \theta * D(Jan),,$$

where I_{t-1}= 1, if $\varepsilon_{t-1} < 0$, and I_{t-1}= 0 otherwise.

The following restrictions apply: $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$, $\alpha + \gamma \geq 0$.

3.2.1.4 EGARCH Model

Another useful framework to analyse volatility clustering is the following EGARCH model:

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_{12} D_{12t} + \varepsilon_t,$$

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \theta * D(Jan),,,$$

where γ captures the asymmetries: if negative shocks are followed by higher volatility then the estimate of γ will be negative. This model does not require any restrictions.

We use the same approach to test for day-of-the-week and turn-of-the-month effects. The exact specification of each model is given in Table 2. The only difference compared to the previous case is that for the day-of-the-week effect $\beta_1 \ldots \beta_5$ stand for mean daily returns for each trading day of the week, and for the turn-of the-month effect $\beta_{-9} \ldots \beta_9$ measure the mean daily returns for each day around the TOM.

Table 2 Model specifications

	Day-of-the-week effect	**Turn-of-the-month effect**
OLS	$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \cdots + \beta_5 D_5 + \varepsilon_t,$	$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + \cdots + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t,$
GARCH	$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma * D(Mon) + \delta D(Fri) + \theta D(Sat)$	$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma_1 D_1 + \gamma_2 D_2 + \cdots + \gamma_{17} D_{17} + \gamma_{18} D_{18}.$
TGARCH	$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 + \theta * D(Mon) + \delta * D(Fri) + \mu * D(Sat).$	$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2 + \theta_1 D_1 + \theta_2 D_2 + \cdots + \theta_{17} D_{17} + \theta_{18} D_{18}.$
EGARCH	$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}} + \theta * D(Mon) + \delta * D(Fri) + \mu * D(Sat).$	$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \frac{\lvert\varepsilon_{t-1}\rvert}{\sigma_{t-1}} + \theta_1 D_1 + \theta_2 D_2 + \cdots + \theta_{17} D_{17} + \theta_{18} D_{18}.$

The next step is to adjust returns by subtracting the bid-ask spreads as a proxy for transaction costs (see Gregoriou et al., 2004 and Caporale et al., 2015), as in equ. (1).

4 Empirical Results

For brevity's sake, we only include one Table reporting the estimation results for raw and adjusted returns in turn. This is for illustration purposes. All other results are available from the authors upon request. We also provide a summary Table for the complete set of results.

4.1 Empirical Results Without the Adjustment

Table 3 reports the evidence on the January effect for the four models, i.e. OLS, GARCH (1,1), TGARCH (1,1), EGARCH (1,1). It is only found in the mean equation of the GARCH and EGARCH models (but not in the conditional variance equations). Concerning the results for the day-of-the week effect, a Monday effect is found in the mean equations of the GARCH and TGARCH models, and a Friday effect in the mean equation of the EGARCH specification as well. A Monday effect is also present in the conditional volatility of returns. The results for the TOM effect provide some evidence for it in the conditional volatility of returns. The second model, which measures the TOM effect by using a single dummy variable for the last day and the first three days of the month, provides stronger evidence of such an effect.

Table 3 Turn of the month effect before adjustment

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coef	t-Stat	Coeff	t-Stat	Coef	t-Stat	Coef	t-Stat
JANUARY	0.142	0.975	0.172	2.271**	0.108	1.439	0.142	2.106**
FEBRUARY	0.281	2.013**	0.369	8.534***	0.345	7.917***	0.367	9.173***
MARCH	0.216	1.611	0.018	0.196	-0.045	-0.497	-0.079	-0.841
APRIL	0.119	0.88	0.085	1.043	0.074	0.905	0.063	0.8
MAY	-0.108	-0.755	0.024	0.274	-0.018	-0.197	-0.012	-0.14
JUNE	-0.031	-0.221	0.105	1.039	0.049	0.498	0.018	0.192
JULY	-0.047	-0.347	0.034	0.381	-0.004	-0.047	0.017	0.195
AUGUST	-0.084	-0.619	0.116	1.285	0.069	0.763	0.065	0.826
SEPTEMBER	-0.029	-0.213	0.067	0.864	0.071	0.904	0.016	0.227
OCTOBER	0.074	0.565	0.229	2.854***	0.181	2.311**	0.134	1.922*
NOVEMBER	0.064	0.47	0.089	1.064	0.041	0.494	0.037	0.517
DECEMBER	0.165	1.231	0.146	2.009**	0.166	2.077**	0.199	3.261***
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
C			0.083	10.059***	0.084	10.771***	-0.156	-24.643***
ARCH			0.128	24.147***	0.088	12.776***	0.24	30.584***
GARCH			0.863	163.972***	0.866	168.381***	0.983	763.35***
Leverage					0.071	8.034***	-0.045	-8.793***
JANUARY			-0.006	-0.261	-0.014	-0.565	-0.006	-0.595

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

4.2 Empirical results with the adjustment

Table 4 suggests that a January effect is present in the variance equation of the GARCH and TGARCH models. However, the negativity restrictions for these models are not satisfied; this issue does not arise in the case of the EGARCH model that does not have any restrictions on its coefficients. A Monday effect is only present in the conditional variance equation of the EGARCH model. There is less evidence of a TOM effect in the conditional variance equation compared to the case of raw returns. The results based on the second TOM specification suggest that it is not present in the mean equation, but it can still be found in the variance equation, except in the case of the EGARCH model.

Table 4 Turn-of-the-month effect after adjustment

Mean Equation								
	OLS		GARCH		TGARCH		EGARCH	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
JANUARY	0.258	1.49	0.218	0.953	0.191	0.82	0.172	0.89
FEBRUARY	0.108	0.695	0.049	0.271	0.092	0.54	0.245	1.686*
MARCH	-0.178	-1.254	-0.344	-2.61***	-0.258	-2.105**	-0.378	-3.159***
APRIL	-0.061	-0.398	-0.05	-0.295	-0.052	-0.328	-0.07	-0.582
MAY	0.03	0.179	0.023	0.138	0.016	0.106	0.035	0.24
JUNE	0.074	0.44	0.084	0.403	0.1	0.518	-0.086	-0.62
JULY	-0.037	-0.237	-0.043	-0.226	-0.044	-0.251	-0.161	-1.473
AUGUST	0.07	0.43	0.067	0.342	0.084	0.468	0.033	0.288
SEPTEMBER	0.036	0.225	0.056	0.312	0.059	0.356	-0.102	-0.86
OCTOBER	0.186	1.182	0.202	1.052	0.194	1.09	0.057	0.516
NOVEMBER	0.073	0.436	0.059	0.273	0.055	0.277	0.295	2.387**
DECEMBER	-0.126	-0.787	-0.097	-0.722	-0.069	-0.534	0.019	0.141
Variance Equation								
	OLS		GARCH		TGARCH		EGARCH	
			Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
C			2.358	12.12***	1.748	3.25***	-0.003	-0.301
ARCH			0.058	2.087**	0.11	2.149**	0.017	1.423
GARCH			-0.468	-4.372***	-0.21	-0.63	0.976	108.78***
Leverage					-0.041	-0.664	-0.098	-6.064***
JANUARY			1.39	2.193**	1.139	1.937*	0.029	1.106

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Table 5 summarises the complete set of results. In brief, evidence of a January effect is found for the raw returns when using GARCH and EGARCH specifications; however, it disappears when transaction costs are introduced. A day-of-the-week effect is also detected when estimating GARCH and TARCH models for the raw series, but again it disappears when using adjusted returns. Similarly, a turn-of-the month effect is found only for the raw data when adopting GARCH, TGARCH and EGARCH specifications.

Table 5 Summary of the Results

	OLS		GARCH		TGARCH		EGARCH	
	without adj.	with adj.	without adj.	with adj.	without adj.	with adj.	with adj.	with adj.
January effect	-	-	+	-	-	-	+	-
Day-of-the-week effect	-	-	+	-	+	-	-	-
Turn-of-the month effect	-	-	+	-	+	-	+	-

5 Conclusions

This paper investigates calendar anomalies (specifically, January, day-of-the-week, and turn-of-the-month effects) in the Russian stock market analysing the behaviour of the MICEX index over the period 22/09/1997-14/04-2016 by estimating OLS, GARCH, EGARCH and TGARCH models. The empirical results show that once transaction costs are taken into account such anomalies disappear, and therefore there is no strategy based on them that could beat the market and result in abnormal profits, which would amount to evidence against the EMH. Therefore the findings of previous studies such as Compton (2013) overlooking transaction costs were misleading: when adjusting returns by using bid-ask spreads as a proxy for such costs (see Gregoriou et al., 2004) the evidence for calendar anomalies and profitable strategies based on them vanishes, suggesting that markets (specifically the Russian stock market in our case) might in fact be informationally efficient.

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